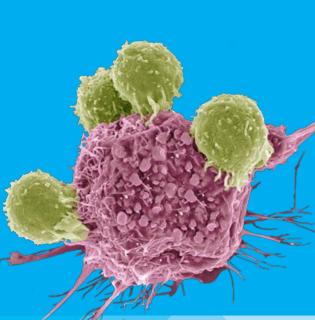
Machine Learning For Personalized Cancer

Vaccines

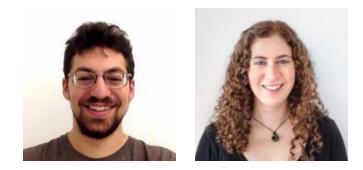
Alex Rubinsteyn February 9th, 2018 Data Science Salon Miami



OpenVax @ Mount Sinai

- Focus: personalized cancer vaccines
 - Machine learning for immunology
 - Cancer genomics
- Enthusiastically translational research
- Open source software: github.com/openvax
- Website: <u>www.openvax.org</u>

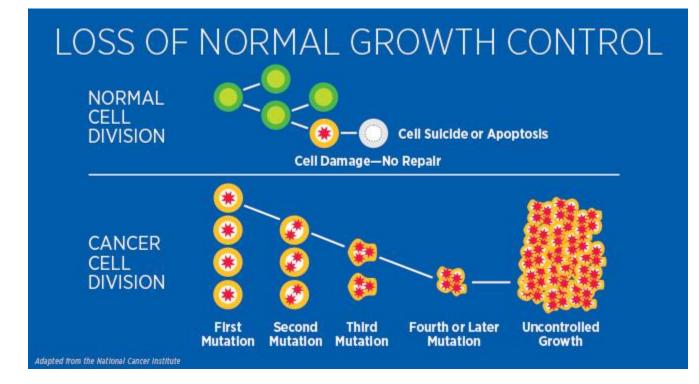




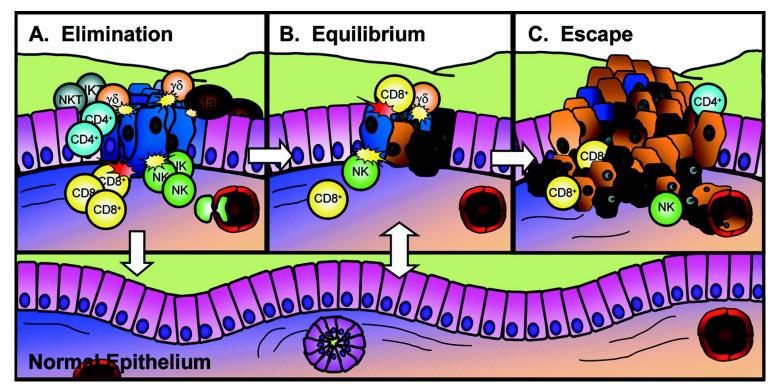


Cancer Immunotherapy

What is cancer?

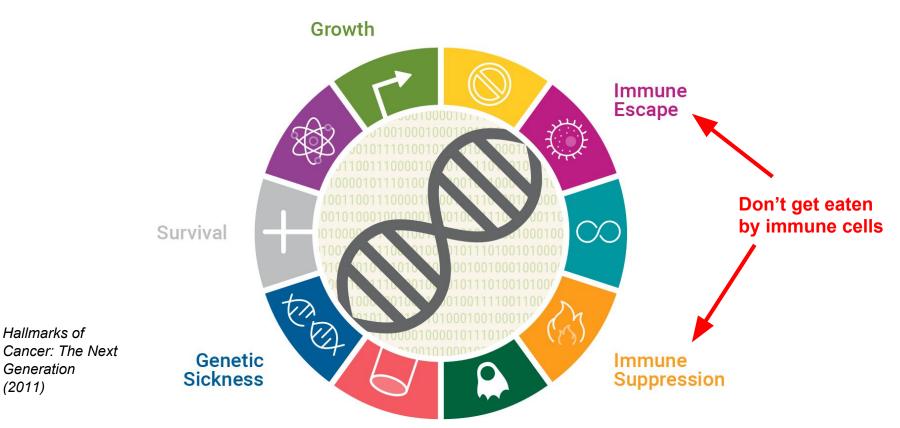


Immune system kills (most) cancer cells



Three E's of cancer immunity, Ian York (2007)

Immune avoidance a hallmark of cancer



(2011)

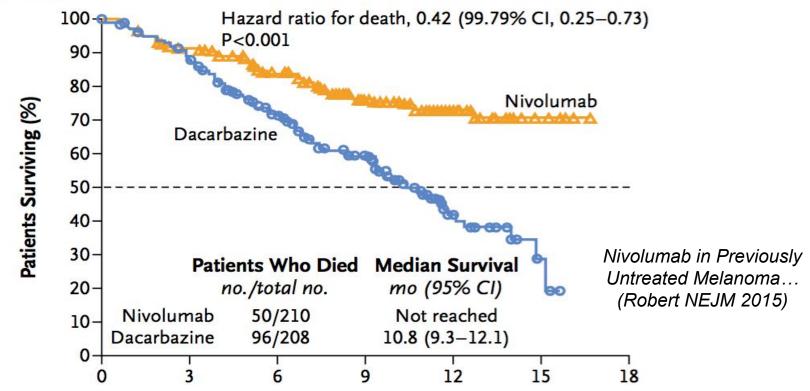
Cancer immunotherapy

- Traditional treatments: focus on killing cancer cells directly
- **Immunotherapy**: get the immune system to kill the cancer

- Why is cancer spreading despite the immune system?
 - Cancer cells inhibiting immune cells
 - Block the inhibitory signals!
 - Immune cells unable to recognize cancer as non-self
 - Teach the immune system what to kill

Immunotherapy vs. Chemotherapy

Overall Survival



Therapeutic Cancer Vaccines

Unpacking "therapeutic cancer vaccine"

• Therapeutic

• Treating established disease (not preventative)

Cancer Vaccine

• Teach the immune system to kill cancer

What's in a therapeutic cancer vaccine?

- Tumor antigen
 - What should immune system look for?
- Adjuvant
 - Something the immune system already responds to as dangerous
 - Examples: double-stranded RNA, mineral oil, dead bacteria
- *Objective*: get the immune system to learn that the antigen is bad and cells which have it should be killed

Personalized therapeutic cancer vaccines

Personalized

- Made from scratch for each patient
- Requires profiling of patients & their tumors

• Therapeutic

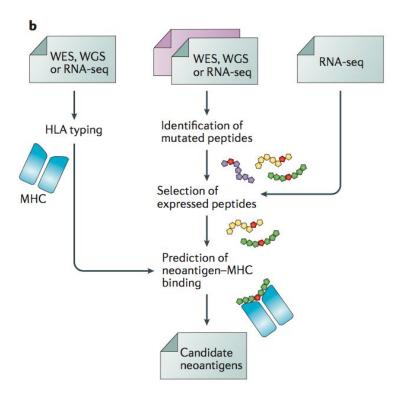
• Treating established disease (not preventative)

• Cancer Vaccine

• Teach the immune system to kill cancer

Choosing what goes in the vaccine

- Sequence patient & tumor DNA
 Identify tumor mutations
- Sequence tumor RNA
 - Which mutations are being produced into proteins?
- Predict which mutations can be seen by immune system



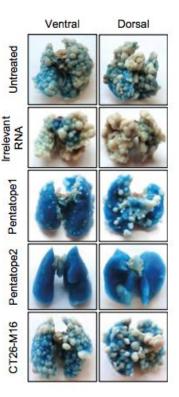
Does it work in mice?

- Details:
 - BALB/c mice
 - CT26 colon cell line
 - mRNA vaccine
- Two groups of 5 mutations

work

 Individual mutatations don't

17 **CT26** IV **RNA** vaccination (c) ns *** ns * Tumor nodules per lung о 200-Untreated understithe Pentatope1 pentatope2 CT26M19



Mutated neo-antigens as targets for individualized cancer immunotherapy (Figure 3.18), Vormehr (2016)

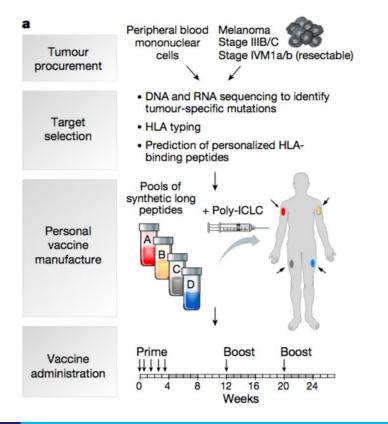
Clinical trial at Dana Farber

An immunogenic personal neoantigen vaccine for patients with melanoma

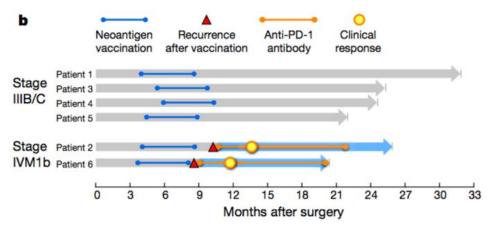
Patrick A. Ott^{1,2,3*}, Zhuting Hu^{1*}, Derin B. Keskin^{1,3,4}, Sachet A. Shukla^{1,4}, Jing Sun¹, David J. Bozym¹, Wandi Zhang¹, Adrienne Luoma⁵, Anita Giobbie–Hurder⁶, Lauren Peter^{7,8}, Christina Chen¹, Oriol Olive¹, Todd A. Carter⁴, Shuqiang Li⁴, David J. Lieb⁴, Thomas Eisenhaure⁴, Evisa Gjini⁹, Jonathan Stevens¹⁰, William J. Lane¹⁰, Indu Javeri¹¹, Kaliappanadar Nellaiappan¹¹, Andres M. Salazar¹², Heather Daley¹, Michael Seaman⁷, Elizabeth I. Buchbinder^{1,2,3}, Charles H. Yoon^{3,13}, Maegan Harden⁴, Niall Lennon⁴, Stacey Gabriel⁴, Scott J. Rodig^{9,10}, Dan H. Barouch^{3,7,8}, Jon C. Aster^{3,10}, Gad Getz^{3,4,14}, Kai Wucherpfennig^{3,5}, Donna Neuberg⁶, Jerome Ritz^{1,2,3}, Eric S. Lander^{3,4}, Edward F. Fritsch^{1,4}†, Nir Hacohen^{3,4,15} & Catherine J. Wu^{1,2,3,4}

- 6 (stage III & IV) melanoma patients
- Up to 20 mutations per vaccine
- Adjuvant: Poly-ICLC (synthetic double-stranded RNA)

Dana Farber Trial: Tumor Control



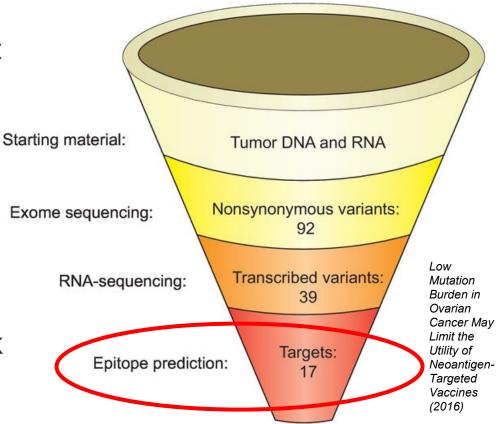
Of six vaccinated patients, four had no recurrence at 25 months after vaccination, while two with recurrent disease were subsequently treated with anti-PD-1 (anti-programmed cell death-1) therapy and experienced complete tumour regression, with expansion of the repertoire of neoantigen-specific T cells.



Machine Learning for Predicting Immune Responses

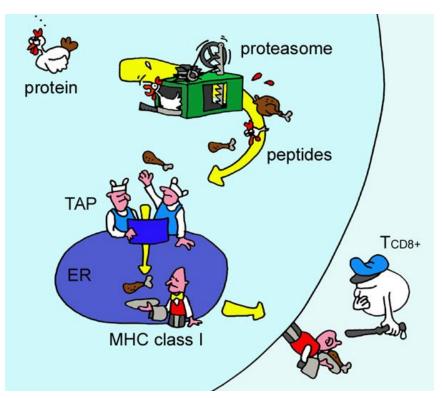
Where do ML models fit in?

- Vaccines typically target
 5-20 mutations
- Depending on the cancer types, we might have hundreds of expressed mutations
- Immune predictions pick the winners



Quick intro to T cells

- Proteins cleaved into peptides
- Some peptides loaded on MHC
- Peptide/MHC complexes presented on cell surface
- T cells look at peptide/MHC complexes
- Abnormal displayed peptides lead to a cytotoxic T cell response

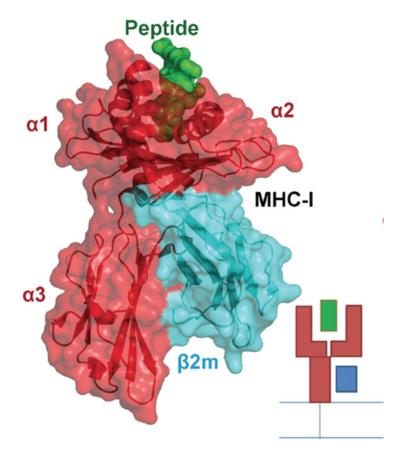


Yewdell, J.W., Reits, E. & Neefjes, J., 2003. Nature Reviews Immunology 19

MHC Binding Prediction

- Thousands of MHC alleles in human population
- Each allele capable of binding a distinct set of peptides

 Objective: Predict whether an MHC allele will bind a given peptide



Immune Epitope Database (IEDB)

- Public dataset of immunology data
- Includes >200,000 in vitro binding affinity measurements of purified MHC/peptides
- Core training data for MHC ligand prediction tools

Summary Metrics	
Peptidic Epitopes	378,287
Non-Peptidic Epitopes	2,543
T Cell Assays	323,210
B Cell Assays	395,472
MHC Ligand Assays	782,035
Epitope Source Organisms	3,627
Restricting MHC Alleles	751
References	18,714

MHC Binding Data

МНС		Epitope	Assay Quantitative measurement		
Allele Name		Description			
	HLA-A*11:01	ADLVGFLLLK	20.300000		
	HLA-A*03:01	ALAETSYVK	35.500000		
	HLA-A*11:01	ALAETSYVK	16.400000		
	HLA-A*02:01	ALAETSYVKV	333.300000		
	HLA-A*02:01	ALGLVCVQA	333.300000		
	HLA-A*02:01	ALGLVCVQM	5000.000000		
	HLA-A*02:01	ALREEEGV	238.100000		
	HLA-A*03:01	DLVGFLLLK	2750.000000		
	HLA-A*03:01	DLVGFLLLKY	1594.200000		

T Cell Response Data

antigen	assay	mhc	organism	peptide	response
Assembly protein G7	IFNg release	HLA- A*26:01	Vaccinia virus	ESKAKQLCY	Negative
Protein A40	IFNg release	HLA- B*40:01	Vaccinia virus	IETPNELSF	Negative
Major core protein 4a precursor	IFNg release	HLA- A*03:01	Vaccinia virus	VTNLISETLK	Negative
NaN	CCL4/MIP- 1b release	HLA- A*02:01	Homo sapiens	ILAKFLHWL	Positive
Protein F16	IFNg release	HLA- A*33:03	Vaccinia virus	RFVNKLKMYK	Negative

Linear models perform reasonably well

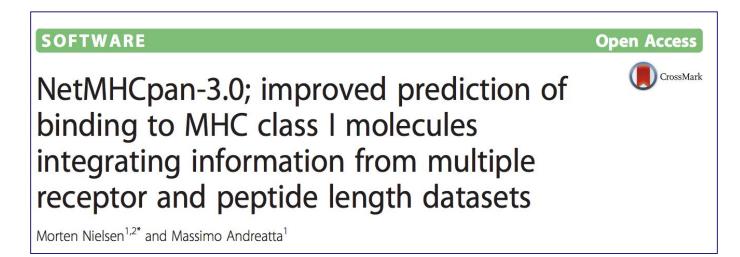
- One-hot encoding of amino acids at each position
- Ignore dependencies between positions
- AUC ~= 0.85-0.9

	HLA A*0201								
	1	2	3	4	5	6	7	8	9
A	-0.3	0.8	-0.3	-0.3	-0.2	-0.3	0.0	0.0	-0.9
C	0.2	0.9	0.0	0.3	-0.5	-0.1	0.1	0.2	0.4
D	0.8	0.9	-0.4	-0.3	0.3	0.2	0.4	0.3	0.6
E	0.6	-0.4	0.7	-0.2	0.1	-0.4	-0.2	-0.2	-0.5
F	-1.3	0.5	-0.5	0.1	-0.1	0.0	-0.3	-0.4	-0.8
G	-0.2	0.1	0.3	-0.1	0.0	0.4	0.3	-0.1	0.2
н	1.1	0.9	-0.1	0.4	0.1	0.2	0.0	0.2	0.8
1	-0.4	-0.7	-0.4	0.1	-0.1	-0.4	-0.5	0.5	-1.4
ĸ	-0.3	0.0	1.1	0.1	0.1	0.6	0.9	0.2	0.9
L	0.0	-1.9	-0.4	-0.2	0.0	-0.2	0.0	-0.1	-1.1
M	-0.7	-1.2	-0.7	0.2	-0.6	0.0	0.0	0.0	-0.8
N	-0.1	0.3	0.1	-0.3	-0.1	-0.3	0.0	0.2	0.7
P	1.2	0.5	0.6	-0.3	0.4	0.0	-0.4	-0.5	0.7
Q	0.4	-1.1	0.0	-0.1	0.4	-0.2	-0.3	0.2	0.7
R	-0.2	0.9	1.0	0.3	0.1	0.4	0.7	0.0	0.9
S	-0.3	0.1	0.1	-0.4	0.1	0.3	-0.2	-0.1	0.2
Т	-0.2	-0.5	0.1	0.4	0.1	-0.5	0.2	0.0	-0.1
V	-0.1	-0.9	-0.1	0.2	0.0	-0.3	0.1	0.1	-1.9
w	0.0	0.7	-0.5	-0.2	-0.1	0.2	-0.3	-0.1	0.4
Y	-0.3	0.2	-0.6	0.2	0.0	0.4	-0.4	-0.3	0.8

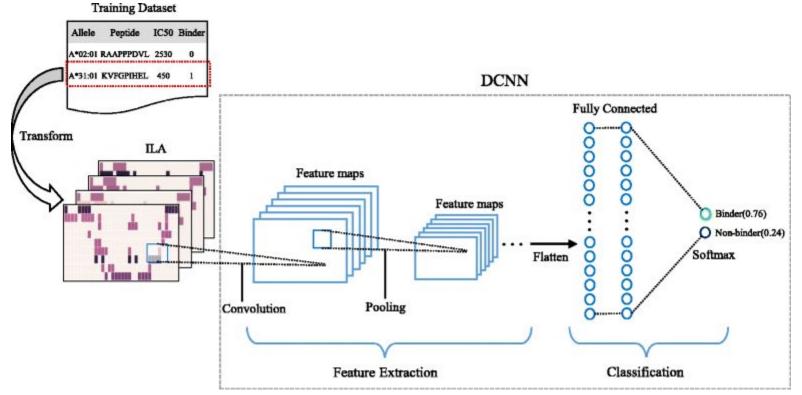
Bjoern Peters

Neural networks do better: NetMHCpan

- Standard tool to predict peptide/MHC binding affinity
- Inputs: peptide sequence and binding groove residues of MHC



Deep learning meets immunology



Deep convolutional neural networks for pan-specific peptide-MHC class I binding prediction

Python Tools for Immunology ML

• Pandas

• Load and filter messy immunology data

• Seaborn

• Visualization

Scikit-learn

Model selection, metrics, shallow (linear & tree) models
 Keras or PyTorch

• Deep learning / neural networks

Startup Landscape

Funding for Personalized Cancer Vaccines



+ ~20 more companies

